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The Rise of Fintech Lending to Small Businesses: Businesses' Perspectives on Borrowing

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Online lending through fintech firms is a rapidly expanding segment of the financial market that is receiving much attention from investors and increasing scrutiny from regulators. Research is only beginning to assess how fintech firms' entry is altering the choices and outcomes of small businesses that borrow from them. The Federal Reserve Small Business Credit Survey is a unique data source on the experiences of business owners with new and more traditional sources of credit. We find that the businesses using online lenders are not representative of small and medium-size enterprise in the US. Businesses borrowing online are younger, smaller, and less profitable. Through reaching borrowers less likely to be served by traditional lenders fintech lenders have substantially expanded the small business finance market. We apply treatment effects estimators to flexibly control for composition differences in the borrowers. After controlling for compositional differences between online and bank borrower, we find that loan application amounts are generally smaller with fintech lenders; businesses that receive fintech loans expect more revenue and employment growth than those receiving a bank loan; and businesses that borrow from banks are more satisfied than businesses that borrow online, which are still more satisfied than businesses who were denied credit. These results highlight issues that the financial industry and regulators should examine as fintech lending to small businesses continues to expand.

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1. Introduction

Fintech is used to describe the rapidly growing set of technology firms providing alternatives to traditional banking services, most often exclusively in an online environment. Fintech firms compete in financial services markets ranging from consumer payment and asset management to business lending and they originated over $41 billion in loans in 2017 (Dixit, 2018). Firms focusing on lending to small and medium enterprise (SME) originated $6.5 billion of loans in 2017, with rapid growth expected in 2018 and 2019. Despite substantial investments and growing activity levels, the sector has been lightly regulated, and there are relatively few studies with any results on fintech as a financing alternative for small businesses (US Treasury, 2016; Jagtiani and Lemieux, 2016; Wiersch and Lipman, 2015; Mach et al., 2014; and Kavuri and Milne, 2019). In addition, constrained by data sources, the research on fintech lending has largely studied the behavior of specific lenders have released information, rather than the set of possible borrowers.[1] In addition the entrance of new financing source raises important regulatory issues as both a source of increased competition (Philappon, 2016) and potential coordination challenges (Basel Committee on Banking Supervision, 2018).

Much of the relevant research has focused on the role of banks in the financing and growth of small businesses, but these approaches have not brought to the role of online lenders. Community banks have long been recognized as an important source of credit for small businesses (Berger and Udell, 2002; Wiersch and Shane, 2013). Despite a growing market share for large banks in small business lending dating back to the 1990s, several

[1] Jagtiani and Lemieux, 2016 and Mach et al., 2014 both examine LendingClub's publicly available data.

studies have shown that community banks still have an advantage in providing appropriate credit products for small businesses (Deyoung et al., 2011; Deyoung et al., 2008; Berger et al., 2005). We examine how the parts of traditional financing (large banks, small banks, and credit unions) differ from online lenders in providing financing for the full range of small businesses.

Fintech firms are now a substantial source of financing for small businesses. According to the Federal Reserve's 2018 Small Business Credit Survey Report on Employer Firms, about 32% of small businesses that sought financing applied with a fintech or online lender,[2] versus 44% with small banks and 49% with large banks. A critical question for regulators to consider is the extent to which fintech lenders have expanded credit access versus substituting for other sources of credit. However, it is equally important for businesses and regulators to know how these new lending alternatives have been working for the small businesses that use them.

To collect data on the financing needs and experiences of small businesses, Federal Reserve Banks have conducted an annual survey of small businesses (the Small Business Credit Survey or SBCS), which reached national coverage starting in 2016. Throughout 2016 to 2018, the SBCS asks about both traditional and online lenders. It is focused on measuring both the financial needs and outcomes of businesses with fewer than 500 full- or part-time employees.[3] While these surveys include thousands of small businesses, they are not a stratified random sample of small businesses. Instead, the survey participants are collected through partner organizations and then the sample is weighted to reflect national

[2] Throughout the paper, we use the terms fintech lenders and online lenders interchangeably.

[3] The survey includes non-employer firms, but for this analysis we focus on businesses with at least one employee.

small business characteristics according to Census data. At this point, we are aware of no alternative data sources on the experiences of small businesses with both fintech firms and banks.

We use 2016 to 2018 SBCS data to analyze the extent to which borrowers from online sources (the phrasing used in the survey for fintech firms) would have been likely to see their needs met by traditional lenders (a category that includes large and small banks and credit unions). We then compare impacts of online lending with traditional finance, which we define to be large and small banks along with credit unions. Raw summary statistics from the Federal Reserve's 2018 Small Business Credit Survey reveal that online loans are associated with higher self-reported growth prospects of respondents but also show that successful borrowers are more satisfied with traditional sources of financing than online financing. However, the availability of financing alternatives is likely to vary substantially based on the size, age, revenues, and other characteristics of the management and of the firm. In order to make meaningful comparisons to other funding sources, compositional differences of businesses that take various financing options or are denied credit need to be accounted for. We apply treatment effect estimators to flexibly control for compositional differences in the borrowers to access the impacts and customer satisfaction differences associated with online lenders.

2. Small Business Credit Survey Design and Coverage

The Federal Reserve's Small Business Credit Survey (SBCS) is an annual survey of establishments[4] with fewer than 500 employees that collects information about business performance, financing needs and choices, and borrowing experiences. The survey is designed to inform policymakers about how the small business credit environment impacts firm operation and growth.[5]

The Federal Reserve partners with over 400 organizations—including chambers of commerce, industry associations, development authorities, and other civic and nonprofit partners—to field the SBCS via an online questionnaire. The sampling frame consists of businesses on the membership list or registry of partner organizations and is, therefore, a convenience sample. Across each participating Federal Reserve district, businesses receive an email from partner organizations on behalf of the respective Federal Reserve Bank requesting their participation and providing an online link to the survey. Response rates for each partner organization are tracked in real time, and partners with initially low response rates may be encouraged to send out additional emails to businesses on their distribution lists until the survey officially closes. In total, responses were collected from 6,614 employer firms in 2018, 8,169 employer firms in 2017, and 10,303 employer firms in 2016 across all 50 states and the District of Columbia.

Unweighted, the SBCS sample is likely to reflect the firms favored by the Federal Reserve's collection process. For example, given that the sampling frame primarily consists

[4] In the remainder of the paper, we use the terms "firm" and "business" interchangeably to refer to surveyed establishments.

[5] See https://www.fedsmallbusiness.org/ for more information.

of distribution lists of chambers of commerce and industry associations—organizations less likely to be connected to younger, less established firms—it is reasonable to expect that such firms would be underrepresented in the SBCS sample. In order to correct for gross sampling deviations from population data, the Federal Reserve uses a ratio-adjustment=weighting method along the demographic dimensions of age, employee size, and industry to make the sample more representative of the population distribution of firms.[6] Age of firm data come from the Census Bureau's Business Dynamics Statistics. Industry and employee size data are from County Business Patterns.

3. Adoption of the Fintech Alternative to Banks

There is no question that fintech lenders are increasingly active in small business finance, but a critical policy issue for financial regulators is whether fintech firms have expanded access to credit for small businesses. The Treasury report on nonbank financials, fintech, and innovation (US Treasury, 2016)—and a 2019 interagency statement from the five federal financial regulators[7]—cites the deployment of alternative models and data sources as a mechanism to expand credit availability particularly for consumers and businesses that might be constrained by traditional credit scoring models.[8] In the recommendations section, the Treasury report "recognizes that these new credit models and data sources have the potential to meaningfully expand access to credit and the quality

[6] Most econometric studies instead weight by an observation's inverse probability of selection. The SBCS poses certain limitations in this regard.

[7] See CA Letter 19-11 Interagency Statement on the Use of Alternative Data in Credit Underwriting: https://www.federalreserve.gov/supervisionreg/caletters/caltr1911.htm

[8] US Department of Treasury, *A Financial System That Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation*, (July 2018), page 136.

of financial services."[9] However, identifying when fintech loans are an expansion of credit versus substitution from banks and other providers of credit has not been previously quantified in this market. In the context of consumer loans, Jagtiani and Lemieux (2018) show that while there are substantive differences between LendingClub and general personal loan borrowers (penetrating potentially undeserved areas), LendingClub borrowers' "average FICO score is only very slightly below the average of overall Equifax customers." This could be interpreted as evidence that much of the expansion might be substantially drawn from traditional banking alternatives.

The SBCS provides information on the businesses that receive financing from an online lender. This information can be used to compare these businesses to characteristics of receivers of bank loans and to the characteristics of businesses that were denied financing. In simple comparisons, online borrowers are on average younger firms, with fewer employees, less revenue, and higher credit risk (Table 1). In terms of industry, firms in healthcare, administrative services, and retail are the most likely customers for fintech loans. A larger proportion of firms operating at a loss also tend to turn to online lenders compared to firms receiving loans from traditional lenders, as do a larger proportion of minority-, women-, and veteran-owned businesses. The differences support the argument that online lenders reach groups that are less likely to be served by banks, but these firm characteristics are correlated with each other so a model is needed to evaluate the relative importance of these factors on the type of financing received, if any.

[9] US Department of Treasury, *A Financial System That Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation*, (July 2018), page 136.

3.1 Which Businesses Receive Which Financing?

We do not observe the specific factors which banks or online lenders use in their lending decision, but any of the business characteristics identified in Table 1 could be a factor in lender decisions. At the same time, correlations between firm characteristics may result in indirect associations of outcomes with observed characteristics that are not actually the factors used to make lending decisions. We apply a multinomial logit model for financing outcomes to identify the factors with the greatest impacts on the funding outcomes of the small businesses that applied for financing. We specify a firm's financing status as a function of size (in terms of employees), age, industry, revenue, profitability, credit risk status, and the demographic variables minority owned, woman owned, and/or veteran owned with all covariates specified as categorical variables around conventional cutoffs. In addition, we include controls for changes in state unemployment rates to account for local economic conditions.

The multinomial logit model implies that the probability of an outcome, also known as the propensity score, is:

$$P(w = 1 |\, x_i) = \frac{e^{X_i \beta_1}}{1 - \sum_{o=1}^{O-1} e^{X_i \beta_o}}.$$

The sum of the probabilities of all outcomes w is equal to one by construction. In our estimation, financing outcomes are online, bank or credit union, and denied: $w_i = O, B$, or D.

Table 2 shows the average marginal effects of the key variables.[10] Average marginal effects are measured as the difference in propensity scores for a predicted outcome (w=O) for a particular variable (z=1) versus (z=0), averaging across all observations of other variables x regardless of the realized outcome of the observations:

$$AME(w = O, z = 1) = \sum_{n=0}^{N} \big(P(w = O|z = 1, x_n) - P(w = O|z = 0, x_n)\big)/N$$

Because the sample is composed of all businesses applying for credit regardless of outcome, it represents the average effect of a categorical variable for an otherwise typical business applying for credit. The average marginal effects also net to zero across rows because the columns represent the full set of options.

The borrowing outcomes of small businesses do depend on a range of characteristics, but not necessarily monotonically. The effect of a business being in one of the younger age categories (firm age between 3 and 20 years) is to boost the likelihood of receiving credit from an online lender and lower the likelihood of bank financing. In contrast, most age groups of firms are not statistically distinguishable for being denied financing, with statistically significant results only for firms between 16 and 20 years old (-4 percentage points). The oldest age categories of small businesses are most likely to receive bank financing (7 percentage points).

Increased employee counts (included as a continuous variable and its square) make bank financing statistically more likely, with similar reductions in being denied financing or the use online financing. The negative coefficient on the squared term of employment size

[10] The multinomial logit model's full results are shown in appendix Table A1. The samples vary some based on the outcome questions. We include the largest possible sample for each outcome, so there are four similar but not identical logit models shown in Table A1.

(Table A1) implies that these effects diminish as firms grow. That said, for most of the firm sizes in our sample, these effects are not that large: Going from 1 employee to 10 employees increases the likelihood of bank financing by about 2 percentage points and lowers the likelihood of online financing by 1 percentage point.

The profitability of businesses is a critical factor for banks, boosting the likelihood of bank financing by about 6 percentage points. That higher probability of bank lending is mirrored by lower likelihoods of both denials (-4 percentage points) and online-lender financing (-2 percentage points) for profitable firms. The coefficients imply that online-lender financing is more likely for unprofitable firms, all else held constant. Even accounting for profitability, higher-revenue firms are 9 percentage points more likely to receive bank financing, with most of the offsetting probability coming from denials. Finally, being evaluated by a credit bureau as medium or high risk substantially lowers the likelihood of bank financing (by 11 percentage points) and evenly raises the likelihood of both denial and online-lender financing. These key financial outcome variables clearly help to determine which firms receive which financing outcomes.

The demographic characteristics of the heads of businesses are relatively less influential on the outcomes, but there are still some statistically significant differences after accounting for the other variables. Minority status lowers the likelihood of bank financing by roughly 4 percentage points, with the associated higher frequency being in denials. Women-owned businesses have a lower likelihood of being denied financing, while veteran-owned businesses are more likely to receive online financing with an associated lower probability of bank financing.

We included the change in state unemployment rates to account for (generally) improving market conditions on lending outcomes. Banks seem to be less likely to lend in areas that are experiencing declines in unemployment rates (with associated higher levels of denials), but the changes are relatively small in most of this period a finding that suggests a relatively small role for local economic conditions in the determination of individual small business lending outcomes.

Finally, we included year dummy variables to account for other changes over time. This variable seems to primarily pick up the relative rise in online lending relative to bank lending. All else equal, the outcome of getting online financing is 12 percentage points more likely in 2018 than it was in 2016, with most of that effect being accounted for by offsetting reductions in the likelihood of being a bank borrower. While this is the result of the expansion of online lenders, our other finding reveal that the increasing usage of online lenders was not uniformly spread across all types of small businesses

3.2 Are Online Lenders Expanding the Financing Options of Small Businesses?

The substantial differences seen in the probabilities reported in Table 2 motivate the importance of the controls and we can use the associated propensity scores to evaluate the proportion of online-lender financing that could be substituting for bank financing rather than representing a new source of business financing. The relevant comparison uses the propensity of borrowers to receive bank financing given the full set of characteristics of each small business[11]: $(P(w = B|x_n,)$. These propensities can then be compared for

[11] We group the financing received from large and small banks with credit union financing into the category of traditional financing. Credits unions remain a smaller actor in small business financing but are important enough to include: 8% of our businesses seeking financing received their first financing from a credit union.

businesses that received financing online and those that received financing from banks, along with those rejected for financing.

Figure 1 shows the densities of propensity scores for receiving bank financing for businesses that received small or large bank loans, online loans, or were denied financing. The density uses the propensity scores produced by the model but smooths those figures using a Gaussian kernel. The kernel density estimator is used to deemphasize small differences in specific *z values* that the model is likely to produce given the discrete data it includes.

Not surprisingly, the majority of businesses that actually received financing from either large or small banks have propensity scores for traditional financing of above 0.70. The median propensity scores for a business that receives traditional financing is 0.77. In contrast, online lenders appear substantially more likely to provide credit to firms that the model expects to be denied credit. The median bank financing propensity score for businesses that use online-lender financing is 0.51, which is identical to the median propensity score of businesses that were denied credit. This means that half of those either using online financing or denied financing were evaluated by the model as being in a region of characteristics where bank financing is uncommon.

To formalize this point we construct a measure of added lending activity (A) associated with the existence of online lenders. It sums the excess mass of the online lender outcome, whenever the density for online lenders is higher than traditional lenders:

$$A = \sum \big(f_{w=O}(z_d) - f_{w=B}(z_d)\big) \cdot I\big(f_{w=O}(z_d) > f_{w=B}(z_d)\big),$$

where $z_d(x) = P(w = B|\, x_d)$ and the densities, f, are estimated using a kernel density procedure. The summation can then be applied across the full dataset. For the period of

2016 to 2018, we would estimate that 44 percent of businesses served by online lenders look unlikely to have been served by banks. This is a conservative estimate of the extra firms financed, because the entry and expansion of online lenders has likely also drawn more businesses into to apply for financing than would have been the case without the new option.

For Figure 1 we grouped all of the existing traditional financing options together, but given the longstanding research on the roles of small banks and the relatively recent entry of credit unions into small business finance, it is worthwhile to compare these lenders. Figure 2 shows the densities of business propensity scores for traditional financing by the type of institution that provided each business's first financing. This comparison is offered as a way to assess whether the banking options are similar. It is the case that small and large banks are essentially equally likely to provide financing at any given level of the propensity score. Figure 2 does reveal that credit unions more frequently lend to businesses with a lower propensity score for traditional financing. That said, the difference between these categories of lenders is much smaller than the difference between traditional financing and online lending.

3.3 How Are Online Lenders and Banks Changing over Time?

Online lenders are a new and growing alternative, so we might expect changes in their lending as they gain experience or become more integrated into the regulated banking industry.[12] Likewise, we might expect changes in bank lending as banks respond to new competitors. To compare the outcomes for online borrowers versus bank borrowers

[12] For example, LendingClub's pending acquisition of Radius Bank would likely require LendingClub to become a bank holding company.

between 2016 and 2018, Figure 3 contrasts the propensity to be denied financing for these outcomes over time. In the case of online borrowers, the modeled likelihood of denial for the businesses that received funding declined from 2016 to 2017, and again from 2017 to 2018. On balance, businesses that are less likely to be denied are a larger share of online lender activities, even though online lenders continue to work with clients that are more likely to be denied than banks, which are shown in the lower panel of Figure 3. Given that this is based on the combined decisions of the lender and borrower, we need to be careful interpreting these results, but it is clear that the joint-decision outcomes for online-lender borrowers were evolving over this period. In contrast, there is relatively little change in the propensities of denial for bank borrowers, which suggests little reaction on the part of banks or their borrowers to the entry of online lenders. These are early results, but they suggest a continuing need to examine the evolving marketplace for small business lending as changes are still occurring from year to year.

4. Using Treatment Effects to Evaluate Financial Alternatives

The expansion of credit to small businesses is an important question, but policy makers and regulators are also interested in whether a credit source is beneficial and appropriate for the borrower. This is hard assessment to make in the best of circumstances because we only observe one set of outcomes per firm, so the outcomes associated with a counterfactual funding alternative is never observed. Complicating matters many small business that do or don't borrow both have reasonably high rates of failure. The SBCS does not follow firms so we cannot measure failures or defaults, but it does include the businesses' assessments for revenue growth, employment growth, and satisfaction with financing after the lending outcome. Table 3 shows business expectations with no controls applied other than the weighting to match population statistics. Without compositional controls, firms that received online financing have the most positive expectations about future firm growth for revenue, while firms denied financing had the strongest outlook for employment growth. This could be evidence of the value of online financing, but it could also reflect the role of sorting based on the age of the firm: younger\riskier firms expect more growth and are more willing to use online financing. In addition, the overall differences in expectations across treatment groups are not large, so we should be cautious in concluding that the raw differences in survey results constitute a real impact of receiving certain types of financing (or not) on expected growth.

Differences in satisfaction levels across treatment groups are much more pronounced, with only 5.3% of firms denied financing being satisfied with their lender(s) compared to 37.7% among firms approved by fintech lenders, and 69.6% among firms approved by traditional bank lenders. These differences are large, but again we should be concerned about the compositional differences.

4.1 Treatment Effects Estimators

Ideally, we would like to observe the counterfactual scenarios of each firm, that is to say, what the expectations of a firm denied financing would have been if it had been approved by an online lender and likewise if it had been approved by a traditional lender. However, by construction, we will never see all three financing treatments for the same owner because they are mutually exclusive. Furthermore, our data are not the product of a large-scale randomized experiment, which could make other important characteristics of the owner/firm asymptotically irrelevant. These weaknesses imply that confounding variation (like the age and profitability of the business/owner) could impact the likelihood of observing a given financing treatment and, potentially, the outcomes of interest given a financing treatment.

To address these issues we apply semi-parametrically estimated treatment effects given the likelihood that firms with specific characteristics are provided financing w_i= O, B, or D. Specifically, we will estimate potential-outcome means for all firms regardless of outcome, for receiving online financing ($E[Y_i|w_i = O]$), receiving bank financing ($E[Y_i|w_i = B]$), and for seeking financing but being denied ($E[Y_i|w_i = D]$). Using these terms we can evaluate an average treatment effect for online financing as $ATE(O) = E[Y_i|w_i = O] - E[Y_i|w_i = D]$ along with a parallel estimate for traditional bank financing, $ATE(B) = E[Y_i|w_i = B] - E[Y_i|w_i = D]$. Finally we can also construct a relative treatment effect of online financing relative to bank financing: $RTE(O, B) = E[Y_i|w_i = O] - E[Y_i|w_i = B]$.

In our analysis we estimate these values using inverse-probability weighting (IPW) and inverse-probability-weighted regression adjustment (IPWRA) as described in Imbens (2004) and Wooldridge (2015). IPW is simply the sample average of the outcome weighting by $\hat{p}(w, x_i)$, the estimated probability that observation *i* experiences treatment W:

$$\hat{\mu}(W) = N^{-1} \sum_{i=1}^{N} \frac{I(w_i = W) Y_i}{\hat{p}(w, x_i)},$$

where I() is an indicator function.

Weighting by the inverse of the propensity for an outcome, w, given x_i balances the observations across the full range of characteristics regardless of outcome. In our case, $\hat{p}(w, x_i)$ is implemented by the simple multinomial logit model discussed previously. An advantage of IPW is that assumptions about the nature of the outcomes with respect to covariates are limited, given an effective model of the probability of treatment.

IPWRA combines this weighting with regression-based adjustment for differences in outcomes based on the set of characteristics x_i solving the following minimization:

$$\hat{\mu}(W) = \min_{\alpha_1,\beta_1} \sum_{i=1}^{N} \frac{(I(w_i = W)(Y_i - \alpha_1 - \beta_1 x_{i1}))^2}{\hat{p}(w, x_i)}.$$

While there is no particular justification for different control variables in the two steps, x_i and x_{i1} need not be identical. The IPWRA is a "doubly robust technique" in that it is asymptotically unbiased if either the model of treatment probabilities or the model of conditional means is correct (Wooldridge, 2015).

Importantly, regardless of the estimation technique, reliable estimates of these values rely on two assumptions: 1. *Unconfoundedness* or conditional independence, which requires that treatment assignment be independent of the treatment effect when conditioned on appropriate control variables. 2. *Overlap of the treatments*, which requires that probability of observing a treatment value must be greater than zero for all relevant *x*.

In the case of small business lending, firm-specific controls for variables that are likely to alter the approval of loans are key controls that are likely to satisfy assumption 1. We intentionally included all reasonable variables available in the small business credit survey including revenue, profitability, age of firm, and the demographic characteristics of the business owner. These variables should inform predictions of financing approval and were shown in Table 2 to be important factors.

4.2 Overlap of Treatments

For the measurement of the businesses' response to the two lending treatments it is important to confirm that there are relevant observations to compare according to the treatment model. The fundamental issue is that if online borrowers were always riskier than any observed bank borrower, then it would require strong assumptions to estimate what their outcomes would have been had they received a bank loan. A lack of overlap makes it particularly difficult to reliably predict the counterfactual scenarios that are needed to obtain accurate treatment effects.

The plot in Figure 1, while informative about the expansion of credit, is called an overlap plot in the treatment effects literature. It shows the distribution of predicted probabilities of receiving each financing treatment and for denial for firms according to their propensity to receive bank and credit union financing. From an overlap perspective we want to see that there are observations experiencing each outcome for any given propensity of bank and credit union financing. This is generally the case, with the only possible exceptions coming at the far tails of the densities, when none of the outcomes are likely. This is excellent for being able to estimate treatment effects across the full range of firms in the data. Figure 4 completes the set of overlap plots, by showing the plots based on propensities to receive online financing and to be denied financing. The plot on the top displays the estimated density of the predicted probabilities for receiving online financing. The plot on the bottom shows the propensity of denial for the different treatment outcomes. There is again substantial overlap through much of the distribution, although bank borrowers crowd to the left (low online or denial probability) in Figure 4 making conclusions about riskier borrowers less robust. Importantly, while profitability, revenues, and so on have a very strong effect on financing treatment, the observed firms do not have most of their mass at opposite ends of the distribution—but rather each example appears to have substantial overlapping cases for each treatment.

5. Effects of Banking Alternatives on Firm Outcomes

5.1 Loan Size Differences

An important difference in alternative lending channels is the size of the loan. In order to support a higher response rate, the SBCS does not ask for the specific amount of loan applications. Instead it asks in terms of five bins, which increase in width as the loan application amounts rise. The loan application amounts are clearly lower for online loans than for bank loans, but again this is likely to reflect firm differences in addition to any difference in the treatment channel. Nonetheless, the application amount is likely to reflect the firm's estimate of what funding level is feasible with a given lender. Indeed, both banks and online lenders may be quite explicit in what size of loans will be considered.

To counter the tendency for firm characteristics to distort the channel differences we applied inverse probability weighting to the histograms to produce as estimate of the loan size distribution once the composition is accounted for. Figure 5 shows the results of these estimates. It is still clearly the case that applicants at online lenders make smaller requests, with over 70% of loan applications requesting less than $100,000 versus roughly 56% of adjusted loan applications with traditional lenders.

5.2 Revenue and Employment Growth

The firms in our sample are interested in pursuing financing presumably to expand their operations either with capital or with operating support. In the first case, we should expect the business to anticipate revenue growth and potentially employment growth. However it could be the case that the unobserved terms of the financing hinder the growth of firms. With this in mind, we seek to identify the effect of fintech financing on the business outlook for revenue and employment growth. We also measure differences in satisfaction with the lending experience.

Future revenue growth is measured by the owner's short-term expectations (next 12 months) for revenue. Table 4, row 1 reports results for 7,284 of the firms in the SBCS sample that pursued financing and answered the revenue question, when we applied the standard IPW for adjusting for differences. We report the potential-outcome mean for being denied financing and then the treatment effects for receiving online or bank financing, followed by the relative treatment effect between online and bank financing. A clear majority of the composition-balanced businesses (75.2%) expect revenue growth even if they were denied financing. Borrowing from an online lender results in a 2.9 percentage point increase in expectations for revenue growth after accounting for compositional differences, while bank financing lowers expectations by 1.3 percentage points. These treatment effects and their associated standard errors (in parentheses) indicate that there is no statistically significant difference in expected revenue growth for either financing options relative to being denied financing. However, the difference between online and bank financing is 4.3 percentage points higher for online loans, which is statistically significant at the 95% confidence level. Row two of Table 4 reveals that the results are very similar when the IPWRA model is employed, although results are estimated with less precision. This is encouraging because the IPWRA is more flexible in how it accounts for differences, but the results are quite similar.

Small businesses that are expecting significant growth might be anticipated to also plan on expanding their workforce. Table 4, row 3 shows similar results regarding future employment growth. Adjusting for composition, the potential-outcome means for denial of financing are considerably lower for employment growth than for revenue growth, with 52.7 being the potential outcome mean for being denied financing. As with expectations about revenue growth, neither financing option significantly alters the firms' expectations relative to be denied financing, after accounting for compositional differences. Statistically significant differences exist only between the bank and online groups, where there is a gap in employment growth exceptions of 5.4 percentage points in favor of online financing. Again, the IPWRA results, shown in row 4, confirm these results.

We might have anticipated online loans being less effective than bank loans either because they are smaller or because their terms might differ unfavorably, but this conclusion is rejected in our analysis. Still, the estimated impact of fintech financing on a firm's self-reported business outlook in Table 4 is somewhat ambiguous: Firms in the online treatment group do not perform statistically differently from firms that were denied financing.

5.3 Satisfaction with the Lending Experience

There is one more business assessment relevant to the impact of fintech financing, which is the businesses' satisfaction with their financing. The descriptive statistics shown in Table 2 revealed that there were significant differences in satisfaction levels, but this result could also be substantially affected by the characteristics of the treated samples. The SBCS asks firms whether they are satisfied, dissatisfied, or neutral with regard to the lender or lenders applied to. Respondents are specifically prompted as they answer the question to consider the application process as well as terms of repayment for lenders that approved their application. If denied credit, they are prompted to consider only the application process. For firms in each respective treatment group, we measure the percent of firms satisfied with at least one lender they applied with.

It is not surprising that businesses denied credit are unlikely to be satisfied with the application process: After adjusting for composition, just 5.5 percent of applicants for credit are satisfied after a financing denial. Adjusted satisfaction levels are higher for online lenders, with a treatment effect of 35.5 percentage points, which is statistically significantly different from the denial outcome. Bank financing results in a treatment effect on satisfaction of 61.6 percentage points, which is again statistically significant. An important indicator of potential regulatory issues is the relative satisfactions with online lenders versus banks. Here we see a difference, after compositional adjustments, of 26.3 percentage points, with firms more likely to be satisfied with bank lender(s) than with online financing. In this survey there is a very strong and statistically significant hierarchy of ex post satisfaction with financing alternatives. Bank financing is preferred to online financing, which was preferred to being denied financing. The same results are maintained when the IPWRA procedure is applied.

These result suggest room for improvement for online lenders in their customer satisfaction levels. To further investigate where this difference comes from, the SBCS includes an identification of the type of online lender in 2017 and 2018. Table 5 shows the breakdown of satisfaction rates by type of online lender. We neither adjust for composition nor calculate standard errors given the smaller numbers of survey respondents, but merchant cash advance lenders stand out for their relatively low satisfaction figures. That said, average satisfaction rates for all types of online lenders are still below the bank average of 69.6% (unadjusted, from Table 3).

The 2017 and 2018 surveys also follows up with a question on challenges experienced during the application process. Table 6 shows that the top three challenges reported by businesses applying for online loans are high interest rates (32.8%), unfavorable payment terms (19%), and lack of transparency (5.1%). Challenges for bank borrowers are all lower, but their top three challenges were the long wait for decision (6.1%), high interest rates (4.9%) and the difficult application process (4.7%). These differences in satisfaction and the reported challenges that underlie these results are important for both lenders and regulators to consider.

6. Conclusion and Policy Implications

While there are still many open questions about the value and effects of online business lending, particularly in the long run, our results based on the Federal Reserve's Small Business Credit Survey provide some useful insights into this expanding sector of the financial market. Importantly, the businesses that pursue bank or online options or are denied credit are not equivalent entities. In order to accurately compare the outcomes of these businesses, adjustments have to be made to account for compositional differences. While a treatment effects approach cannot solve underlying sampling defects, it can help to evaluate the role of different lending outcomes when the characteristics of firms vary substantially between those outcomes. We believe this approach can help to address important policy issues where data are still limited.

The 2018 Treasury report notes the potential for fintech to expand credit ". . .to borrower segments that may not otherwise have access to credit through traditional underwriting approaches." We show that the entry of online lenders has meaningfully altered the range of firms that receive financing, with 44% of online borrowers not likely to receive credit from traditional sources. This is important to recognize as policy makers consider options that either support or hinder the growth of these alternative financing sources. Given international evidence indicating that many small businesses may be discouraged from borrowing (Freel, et al., 2012), our estimate of the added lending activity associated with the entry of fintech firms could understate the full effect, given the tendency of many small businesses not to apply for credit that they desire. The entrance of fintech firms may have increased applications due to marginal business expectating fewer rejections. Overall, our evidence suggests that the characteristics of online borrowers are closer to those of businesses rejected for credit than those served by banks, which increases the financing available in the small business financing marketplace.

On the effectiveness of online credit, we find that growth expectations from online lenders are better than those for bank borrowers. This is despite controlling for compositional differences that are strongly predictive of which firms receive credit from banks and from fintech firms, including profitability, revenue growth, and self-reported credit scores of the business or owner. This is result is supportive of the position that financial innovation, at least in case, has been beneficial to borrowers, particularly when combined with the greater inclusion shown by fintech lenders. That said, we are limited to a contemporaneous change in business expectations that would ideally be confirmed with a longer-term analysis of the effects of financing alternatives on the realized performance of small businesses.

While the effects on expectations for growth are relatively small, the ordering of customer satisfaction is clear: Bank borrowers are more satisfied than online borrowers, who are more satisfied than businesses that were denied credit. As businesses become more aware of the availability and performance of online lenders, online lenders remain unlikely to be fully competitive with banks without increasing their customer satisfaction levels, at least for the businesses that could qualify for bank financing. Fintech lenders, in contrast to regulated financial institutions, are currently not required by law to disclose specific product terms like the annual percentage rate (APR); prior research suggests that typical small business borrowers in a focus group setting have had difficulty interpreting financing terms of fintech products (Lipman and Wiersch 2015). The SBCS results from 2017 and 2018 indicate that part of the challenge for a small business owner considering different financing options may be whether he or she understands the financing terms of a given fintech loan. A lack of ex ante clarity is consistent with ex post concerns about high interest rates, unfavorable terms and a lack of transparency. Now that such a gap in post-financing satisfaction between fintech and traditional finance has been identified, potential regulatory policies and firm business strategies can aim to narrow the gap while still allowing a broader set of small businesses to be financed.

Bibliography

Basel Committee on Banking Supervision. 2018. "Implications of Fintech Developments for Banks and Bank Supervisors" *Sound Practices* (February). https://www.bis.org/bcbs/publ/d431.htm.

Berger, Allen N., and Gregory F. Udell. 2002. "Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure." *The Economic Journal* 112 (477): F32-F53. . https://doi.org/10.1111/1468-0297.00682

Berger, Allen, Nathan Miller, Mitchell Petersen, Raghuram Rajan, and Jeremy Stein. 2005. "Does Function Follow Organizational Form? Evidence from the Lending Practice of Large and Small Banks." *Journal of Financial Economics* 76 (2): 237-269. https://doi.org/10.1016/j.jfineco.2004.06.003.

DeYoung, Robert, Dennis Glennon, and Peter Nigro. 2008. "Borrower-Lender Distance, Credit Scoring, and Loan Performance: Evidence from Informational-Opaque Small Business Borrowers." *Journal of Financial Intermediation* 17 (1): 113-143. https://doi.org/10.1016/j.jfi.2007.07.002

DeYoung, Robert, Scott Frame, Dennis Glennon, and Peter Nigro. 2011. "The Information Revolution and Small Business Lending: The Missing Evidence." *Journal of Financial Services Research* 39 (1): 19-33. https://doi.org/10.1007/s10693-010-0087-2.

Federal Reserve. 2016. "2015 Small Business Credity Survey: Report on Employer Firms." Special Report, New York. https://www.newyorkfed.org/smallbusiness/small-business-credit-survey-employer-firms-2015.

Freel, Mark, Sara Carter, Stephen Tagg, and Colin Mason. 2012. "The Latent Demand for Bank Debt: Characterizing 'Discouraged Borrowers.'" *Small Business Economics* 38: 399-418. https://doi.org/10.1007/s11187-010-9283-6.

Imbens, Guido. 2004. "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review." *The Review of Economics and Statistics* 86 (1): 4-29. https://doi.org/10.1162/003465304323023651.

Jagtiani, Julapa, and Catharine Lemieux. 2016. "Small Business Lending: Challenges and Opportunities for Community Banks." Federal Reserve Bank of Philadelphia Working Paper. https://ideas.repec.org/p/fip/fedpwp/16-8.html

Kavuri, Anil Savio and Milne, Alistair K. L., Fintech and the Future of Financial Services: What Are the Research Gaps? (February 13, 2019). CAMA Working Paper No. 18/2019. http://dx.doi.org/10.2139/ssrn.3333515

Lipman, Barbara, and Ann Marie Wiersch. 2015. "Alternative Lending through the Eyes of "Mom-and-Pop" Small-Business Owners: Findings from Online Focus Groups." Special Report, Federal Reserve Bank of Cleveland.

https://www.clevelandfed.org/newsroom-and-events/publications/special-reports/sr-20150825-alternative-lending-through-the-eyes-of-mom-and-pop-small-business-owners

Mach, Traci L., Courtney M. Carter, and Cailin R. Slattery. 2014. "Peer-to-peer lending to small businesses." Federal Reserve Board,Finance and Economics Discussion Series No 2014-10. https://ideas.repec.org/p/fip/fedgfe/2014-10.html.

Philappon, Thomas. 2016. "The Fintech Opportunity." National Bureau of Economic Research Working Paper 22476. https://doi.org/10.3386/w22476.

The Economist. 2015. "The Fintech Revolution: A Wave of Startups Is Changing Finance--for the Better." *The Economist* 415 (8937). http://archive.org/details/The_Economist_9TH_May-15TH_May_2015..

U.S. Department of Treasury. 2016. "Opportunities and Challenges in Online Marketplace Lending." White Paper, Washington D.C. https://www.treasury.gov/connect/blog/Documents/Opportunities_and_Challenges_in_Online_Marketplace_Lending_white_paper.pdf.

Wiersch, Ann Marie, and Scott Shane. 2013. "*Why Small Business Lending Isn't What It Used to Be*."Federal Reserve Bank of Cleveland *Economic Commentary* 2013-10. https://doi.org/10.26509/frbc-ec-201310.

Wooldridge, Jeffrey M. 2015. *Introductory Econometrics: A Modern Approach.* 6th. Boston: Cengage Learning.

Table 1: Basic weighted sample characteristics, survey years 2016-2018

	Denied financing	Online lender	Bank/CU financing
Age			
0-2 years	24.4	15.6	15.5
3-5 years	18.8	22.1	12.8
6-10 years	23.9	27.0	21.3
11-15 years	13.1	15.9	14.3
16-20 years	6.0	7.7	10.2
21+ years	13.8	11.7	25.9
Employee size			
1-4 employees	59.1	54.4	37.0
5-9 employees	20.7	22.6	19.7
10-19 employees	10.4	13.0	18.2
20-49 employees	6.9	7.8	14.6
50-499 employees	2.9	2.2	10.5
Revenue			
<$100K	25.1	12.2	9.9
$100K-$1M	53.6	64.7	42.1
$1M-$10M	19.9	21.9	39.2
$10M+	1.4	1.2	8.7
Profitability			
At a loss	38.7	35.6	22.4
Break even	25.2	21.2	16.0
At a profit	36.1	43.2	61.6
Minority-owned business			
Non-minority	74.2	79.2	83.9
Minority	25.8	20.8	16.1
Female-owned business			
Male	74.6	79.2	80.9
Female	16.1	17.7	14.6
Did not respond	9.3	3.0	4.5
Veteran-owned business			
Non-veteran	67.5	72.9	76.1
Veteran	11.5	15.0	10.2
Did not respond	21.0	12.1	13.7
Unemployment rate (change), 2015-16			
mean	-0.447	-0.443	-0.403
Unemployment rate (change), 2016-17			
mean	-0.514	-0.510	-0.516
Unemployment rate (change), 2017-18			
mean	-0.471	-0.464	-0.435
N	1376	1004	4904

Note: Sample characteristics represent the percentage of survey respondents in each treatment group, except for the unemployment rate variables which represent the average change in the state unemployment rate for the state in which a firm is located during the noted time period. Of the firms in the Bank/CU financing treatment group, 164 were also approved for financing by an nonbank online lender after their approval by a bank lender. Of the firms in the Online financing group, 225 were also approved by a bank or credit union after their approval by an online lender.

Table 2: Average marginal effects of key variables on receiving financing, survey years 2016-2018

	Denied financing	Online lender	Bank/CU financing
Age			
0-2 years	0.026	-0.054***	0.029
	(0.018)	(0.015)	(0.020)
3-5 years	0.017	0.051***	-0.067***
	(0.016)	(0.017)	(0.019)
6-10 years	0.002	0.028*	-0.030*
	(0.014)	(0.014)	(0.016)
11-15 years	0.001	0.038**	-0.038**
	(0.018)	(0.019)	(0.019)
16-20 years	-0.041*	-0.001	0.042
	(0.021)	(0.024)	(0.026)
21+ years	-0.019	-0.049***	0.068***
	(0.015)	(0.013)	(0.016)
Employees	-0.001**	-0.001*	0.002***
	(0.001)	(0.001)	(0.001)
Profitable	-0.044***	-0.019***	0.063***
	(0.007)	(0.007)	(0.008)
Revenue > $1M	-0.052***	-0.036***	0.088***
	(0.011)	(0.011)	(0.013)
Minority-owned firm	0.035**	0.001	-0.037*
	(0.017)	(0.015)	(0.019)
Woman-owned firm	-0.024*	0.012	0.012
	(0.014)	(0.014)	(0.017)
Veteran-owned firm	-0.015	0.056**	-0.041*
	(0.020)	(0.024)	(0.024)
Medium/High credit risk	0.057***	0.052***	-0.109***
	(0.008)	(0.008)	(0.009)
Unemployment rate (change), 2015-16	-0.053***	-0.036*	0.089***
	(0.020)	(0.019)	(0.022)
Unemployment rate (change), 2016-17	0.011	0.027	-0.038
	(0.028)	(0.024)	(0.030)
Unemployment rate (change), 2017-18	-0.064**	-0.030	0.093***
	(0.027)	(0.027)	(0.030)
Year			
2016	0.007	-0.058***	0.051***
	(0.010)	(0.009)	(0.011)
2017	0.004	-0.002	-0.002
	(0.011)	(0.011)	(0.013)
2018	-0.011	0.062***	-0.051***
	(0.010)	(0.011)	(0.012)

Note: Standard errors in parentheses. *** significant at p<0.01; ** significant at p<0.05; * significant at p<0.1. Employee and unemployment rate variables are continuous; all other variables are discrete. For full results of multinomial logit estimates, see Table A1.

Table 3: Treatment group comparison, survey years 2016-2018

	Denied financing	Online lender	Bank/CU financing
Outcomes of interest			
Expects future revenue growth (%)	75.8	76.9	73.2
N	1376	1004	4904
Expects future employment growth (%)	52.9	52.1	50.7
N	1343	990	4829
Satisfied with lender (%)	5.3	37.7	69.6
N	1243	1001	4873

Note: Respondents are asked in separate questions how they expect revenue and the number of employees to change over the next 12 months with the option to select "Decrease", "No Change", or "Increase." Comparisons of each outcome of interest represent the % of respondents who selected "Increase." Of the firms in the Bank/CU financing treatment group, 164 were also approved for financing by an nonbank online lender after their approval by a bank lender. Of the firms in the Online financing group, 225 were also approved by a bank or credit union after their approval by an online lender.

Table 4: Likelihood of reporting future firm growth or satisfaction with lender, by model specification and treatment group, survey years 2016-2018

	Potential-outcome mean	Average treatment effect		
	Denied financing	Online vs Denied	Bank/CU vs Denied	Bank/CU vs Online
Expects future revenue growth				
IPW	0.752	0.029	-0.013	-0.043**
		(0.028)	(0.023)	(0.021)
IPWRA	0.750	0.032	-0.010	-0.041**
		(0.024)	(0.019)	(0.021)
Expects future employment growth				
IPW	0.527	0.036	-0.018	-0.054**
		(0.032)	(0.026)	(0.024)
IPWRA	0.518	0.043	-0.009	-0.052**
		(0.030)	(0.023)	(0.025)
Satisfied with lender				
IPW	0.053	0.360***	0.619***	0.259***
		(0.026)	(0.015)	(0.027)
IPWRA	0.055	0.355***	0.616***	0.261***
		(0.025)	(0.015)	(0.026)

Note: Standard errors in parentheses. *** significant at $p<0.01$; ** significant at $p<0.05$; * significant at $p<0.1$. Of the firms in the Bank/CU financing treatment group, 164 were also approved for financing by an nonbank online lender after their approval by a bank lender. Of the firms in the Online financing group, 225 were also approved by a bank or credit union after their approval by an online lender.

Table 5: Types of online lenders applied to by applicants in online treatment group, survey years 2017-2018

	# of Applicants	% of Applicants	% of Applicants Satisfied
Direct lender	360	57.9	41.9
Retail/payments processor	90	14.5	45.6
Peer-to-peer lender	58	9.3	39.7
Merchant cash advance lender	87	14.0	26.7
Other	28	4.5	53.6

Note: Frequency counts and percentages are unweighted. For a survey respondent's two most recent credit applications–if one or both applications were with an online lender–the respondent is asked: *Which type of online lender did you apply to?* The question was not included in the 2016 survey. Percentages in column 2 do not add to 100 because firms were only asked the given question if their application was among their two most recent applications. *Direct lender* includes OnDeck, Kabbage, Blue Vine, etc.; *Retail/payments processor* includes Paypal Working Capital, Square Capital, Amazon Capital Services, etc.; *Peer-to-peer lender* includes Lending Club, Funding Circle, etc.; *Merchant cash advance lender* includes RapidAdvance, CAN Capital, BizFi, etc.

Table 6: Challenges experienced during application process, survey years 2017-2018

	Online treatment group		Bank/CU treatment group	
	# of Applicants	% of Applicants	# of Applicants	% of Applicants
High interest rate	204	32.8	128	4.8
Unfavorable repayment terms	118	19.0	53	2.0
Long wait for decision	28	4.5	161	6.1
Difficult application process	29	4.7	124	4.7
Lack of transparency	32	5.1	35	1.3
Other challenges	15	2.4	81	3.1
Experienced no challenges	114	18.3	745	28.2

Note: Frequency counts and percentages are unweighted. For a survey respondent's two most recent credit applications, the respondent is asked: *Did your business experience any challenges in applying for the [given product]? Select all that apply.* The question was not included in the 2016 survey. Percentages in column 2 and 4 do not add to 100 because firms were only asked the given question if their application was among their two most recent applications.

Table A1: Multinomial logit regressions for probability of receiving financing (i.e., the treatment models used as inputs into outcome models)[a]

	Revenue model	Employment model	Satisfaction model	Application amount model
Online lender				
Employees (continuous)	-0.000	0.002	-0.001	-0.001
	(0.005)	(0.006)	(0.006)	(0.006)
Employees squared (continuous)	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age				
3-5 years	0.649**	0.611**	0.650**	0.646**
	(0.209)	(0.211)	(0.213)	(0.212)
6-10 years	0.612**	0.611**	0.660**	0.641**
	(0.212)	(0.214)	(0.216)	(0.216)
11-15 years	0.664**	0.606*	0.733**	0.726**
	(0.236)	(0.240)	(0.241)	(0.241)
16-20 years	0.690*	0.699*	0.691*	0.676*
	(0.282)	(0.288)	(0.285)	(0.285)
21+ years	0.255	0.251	0.278	0.291
	(0.232)	(0.235)	(0.235)	(0.235)
Revenue size				
$1M+	0.085	0.090	0.056	0.057
	(0.166)	(0.168)	(0.170)	(0.171)
Profitability				
Profitable	0.211	0.186	0.252	0.267*
	(0.131)	(0.133)	(0.134)	(0.135)
Minority-owned business				
Minority	-0.190	-0.193	-0.233	-0.231
	(0.161)	(0.163)	(0.164)	(0.164)
Female-owned business				
Female	0.170	0.174	0.208	0.191
	(0.146)	(0.146)	(0.148)	(0.148)
Did not respond	-0.976***	-0.983***	-0.420	-0.435
	(0.254)	(0.262)	(0.277)	(0.277)
Veteran-owned business				
Veteran	0.339	0.353	0.317	0.316
	(0.204)	(0.206)	(0.205)	(0.205)
Did not respond	-0.340	-0.324	-0.285	-0.281
	(0.182)	(0.186)	(0.186)	(0.187)
Medium/High risk or non-responder	0.035	0.041	0.072	0.077
	(0.129)	(0.131)	(0.131)	(0.131)
Revenue growth in past 12 months				
Increased	0.017	0.048	0.037	0.033
	(0.132)	(0.133)	(0.134)	(0.134)
Change in unemployment rate (continuous)				
2015-16	0.050	0.006	0.073	0.072
	(0.169)	(0.170)	(0.172)	(0.172)

2016-17	0.097	0.096	0.035	0.040
	(0.223)	(0.225)	(0.228)	(0.229)
2017-18	0.138	0.041	0.098	0.126
	(0.236)	(0.238)	(0.240)	(0.239)
Survey year dummy				
2017	0.390*	0.395*	0.362*	0.367*
	(0.158)	(0.160)	(0.161)	(0.161)
2018	0.770***	0.780***	0.772***	0.772***
	(0.152)	(0.153)	(0.155)	(0.155)
Constant	-0.954***	-1.024***	-1.023***	-1.007***
	(0.279)	(0.283)	(0.284)	(0.284)
Bank/CU				
Employees (continuous)	0.011**	0.012**	0.011**	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Employees squared (continuous)	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Age				
3-5 years	-0.196	-0.217	-0.211	-0.232
	(0.169)	(0.171)	(0.173)	(0.173)
6-10 years	-0.032	-0.037	0.005	-0.012
	(0.170)	(0.173)	(0.175)	(0.175)
11-15 years	-0.049	-0.109	0.001	-0.001
	(0.184)	(0.186)	(0.190)	(0.191)
16-20 years	0.368	0.387	0.354	0.350
	(0.221)	(0.227)	(0.225)	(0.225)
21+ years	0.306	0.277	0.301	0.320
	(0.180)	(0.182)	(0.183)	(0.185)
Revenue size				
$1M+	0.740***	0.735***	0.719***	0.718***
	(0.125)	(0.126)	(0.129)	(0.130)
Profitability				
Profitable	0.755***	0.759***	0.792***	0.801***
	(0.105)	(0.106)	(0.109)	(0.109)
Minority-owned business				
Minority	-0.313*	-0.318*	-0.358*	-0.357*
	(0.138)	(0.140)	(0.141)	(0.141)
Female-owned business				
Female	0.153	0.133	0.189	0.177
	(0.125)	(0.126)	(0.127)	(0.127)
Did not respond	-0.387*	-0.382	0.099	0.066
	(0.192)	(0.198)	(0.231)	(0.232)
Veteran-owned business				
Veteran	-0.081	-0.091	-0.138	-0.135
	(0.165)	(0.168)	(0.168)	(0.168)
Did not respond	-0.255	-0.261	-0.199	-0.195
	(0.145)	(0.147)	(0.151)	(0.152)
Medium/High risk or non-responder	-0.951***	-0.935***	-0.890***	-0.890***

	(0.103)	(0.104)	(0.105)	(0.105)
Revenue growth in past 12 months				
Increased	0.151	0.153	0.163	0.171
	(0.104)	(0.105)	(0.107)	(0.108)
Change in unemployment rate (continuous)				
2015-16	0.475***	0.452**	0.505***	0.498***
	(0.137)	(0.139)	(0.142)	(0.142)
2016-17	-0.147	-0.171	-0.221	-0.215
	(0.194)	(0.195)	(0.200)	(0.201)
2017-18	0.538**	0.516**	0.468*	0.501**
	(0.185)	(0.186)	(0.189)	(0.188)
Survey year dummy				
2017	-0.112	-0.118	-0.120	-0.126
	(0.120)	(0.121)	(0.123)	(0.124)
2018	-0.165	-0.153	-0.149	-0.164
	(0.124)	(0.125)	(0.127)	(0.128)
Constant	1.195***	1.173***	1.110***	1.131***
	(0.219)	(0.221)	(0.224)	(0.224)

a Variable specification is identical for all treatment models, but coefficient estimates vary given that the sample size varies depending on the outcome question asked in the survey. Coefficient estimates are relative to the base outcome of not receiving any financing. Standard errors in parentheses. *** significant at $p<0.01$; ** significant at $p<0.05$; * significant at $p<0.1$.

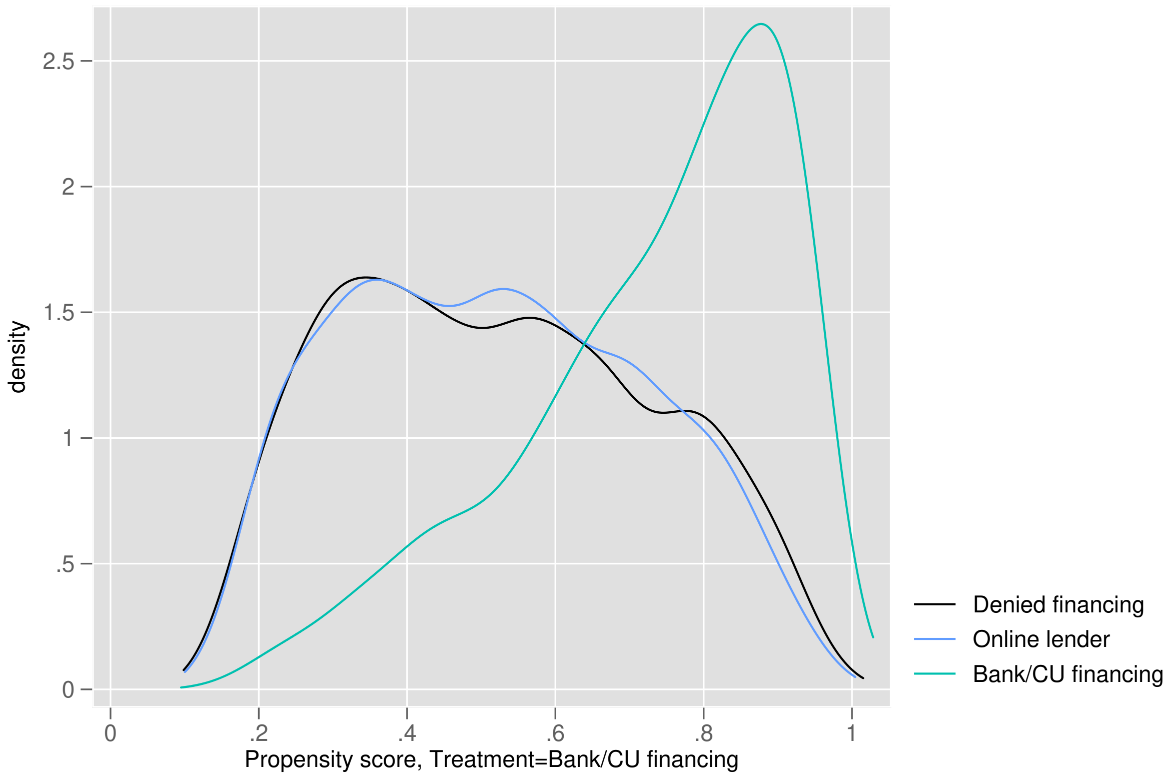


Figure 1: Kernel density ("overlap") plots, survey years 2016-2018. Predicted probabilities of being approved for Bank/CU financing shown for each treatment group. For full results of multinomial logit estimates, see Table A1.

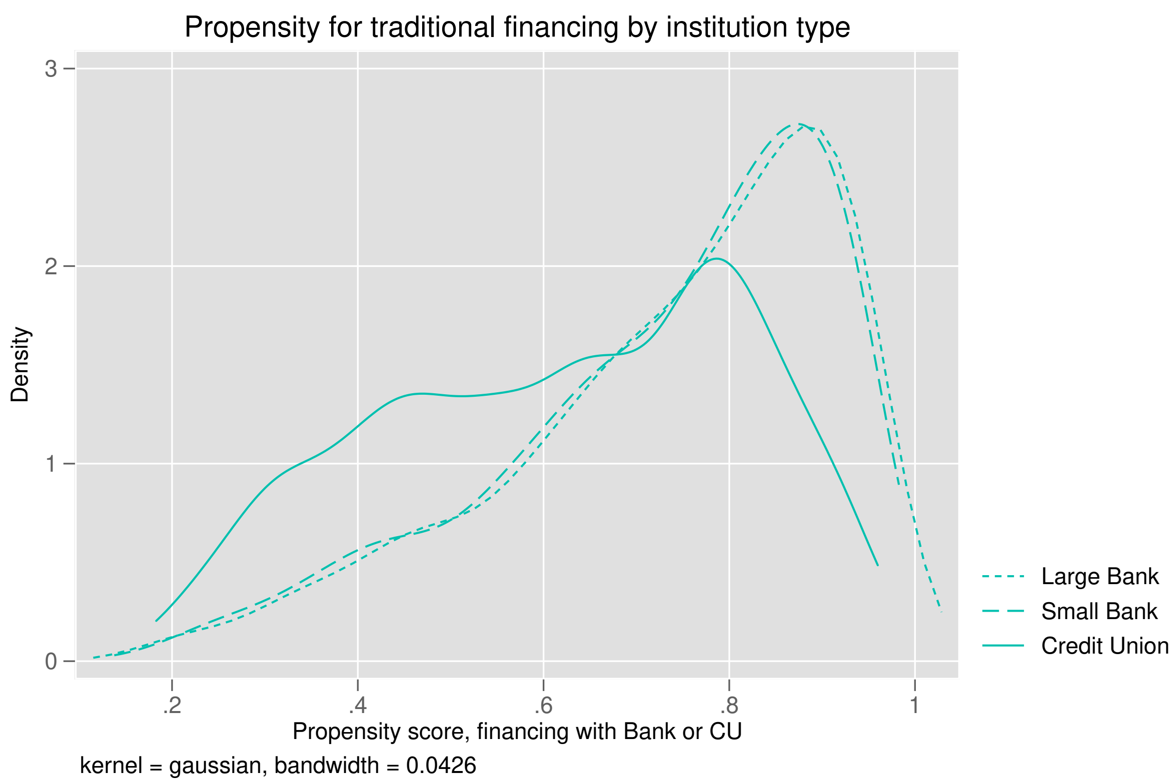
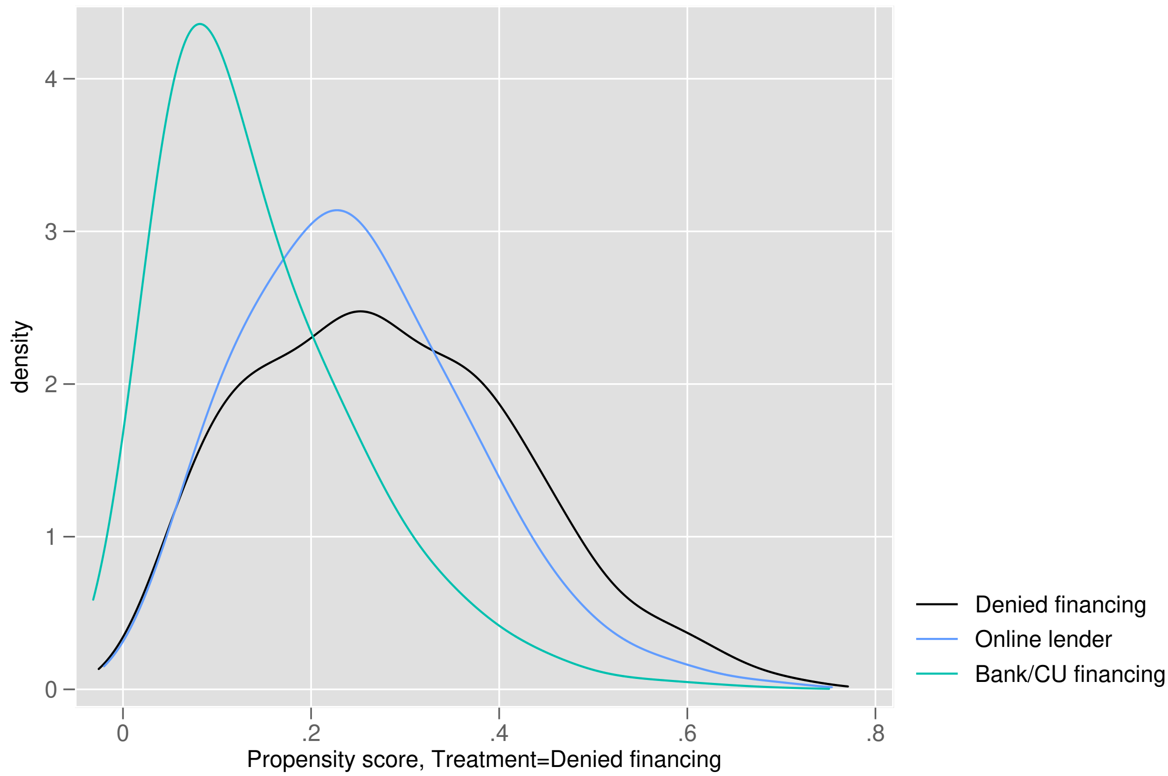


Figure 2: Kernel density plots, survey years 2016-2018. Predicted probabilities of being approved for Bank/CU financing shown for firms actually approved by a small bank, large bank, or credit union. For full results of multinomial logit estimates, see Table A1.



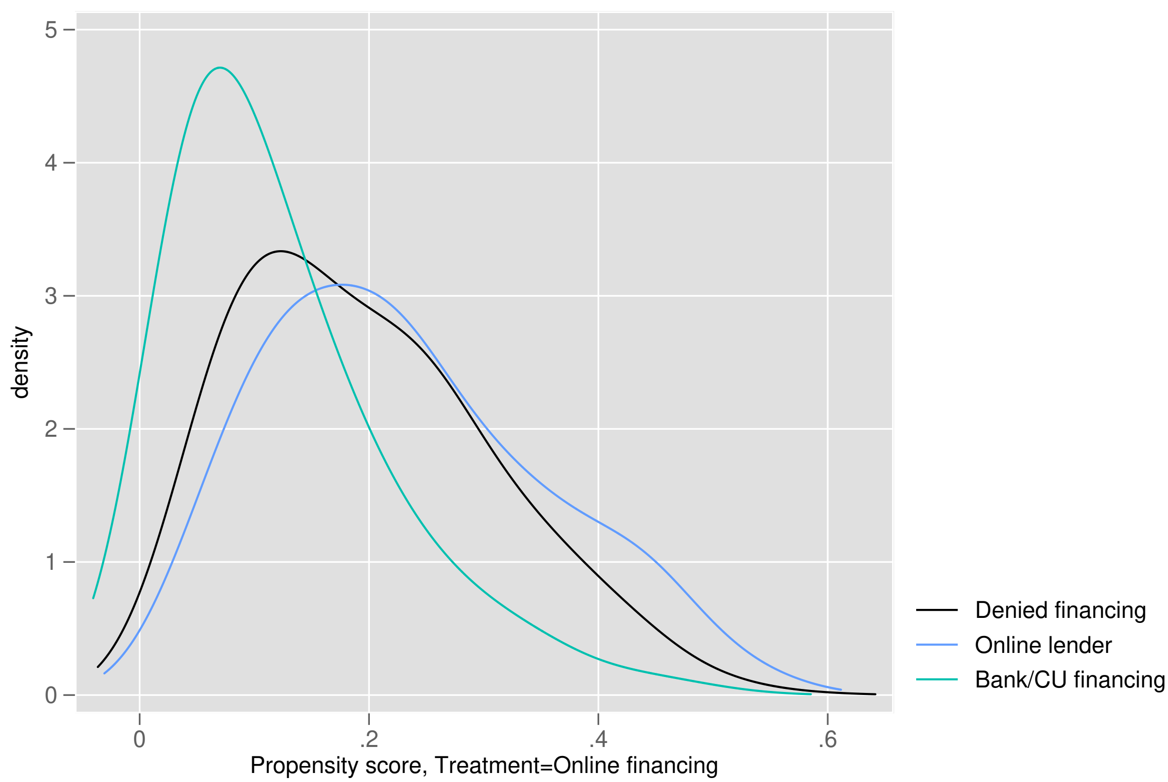
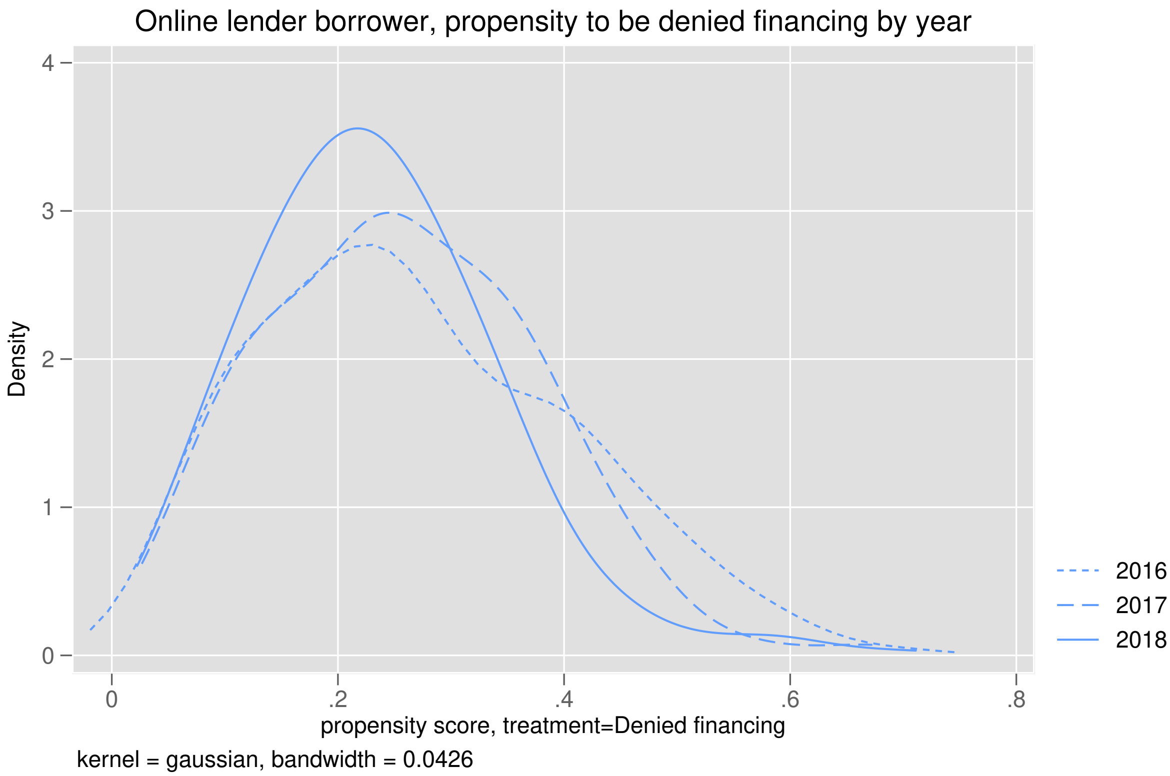


Figure 3: Kernel density ("overlap") plots, survey years 2016-2018. Predicted probabilities of being denied financing and receiving online financing, respectively, shown for each treatment group. For overlap plot of receiving Bank/CU financing, see Figure 1. For full results of multinomial logit estimates, see Table A1.



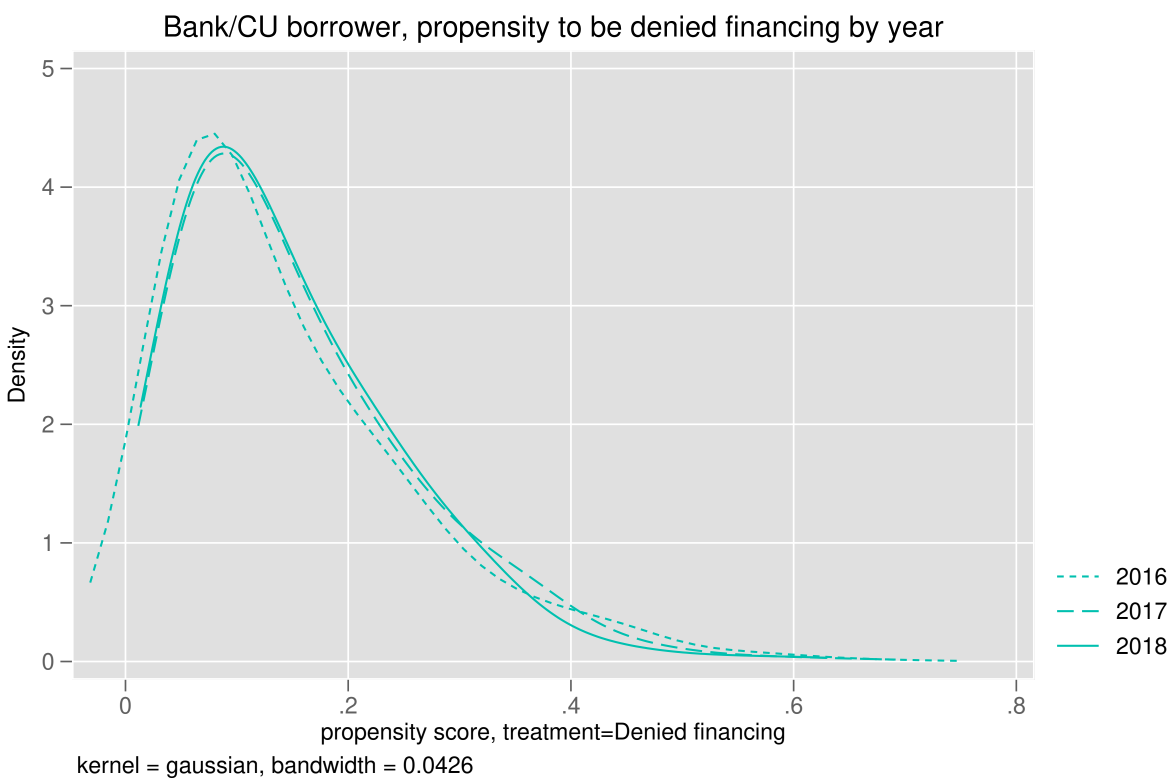


Figure 4: Kernel density plots by year. Predicted probabilities of being denied financing shown for the online lender and large bank treatment group, respectively. For full results of multinomial logit estimates, see Table A1.

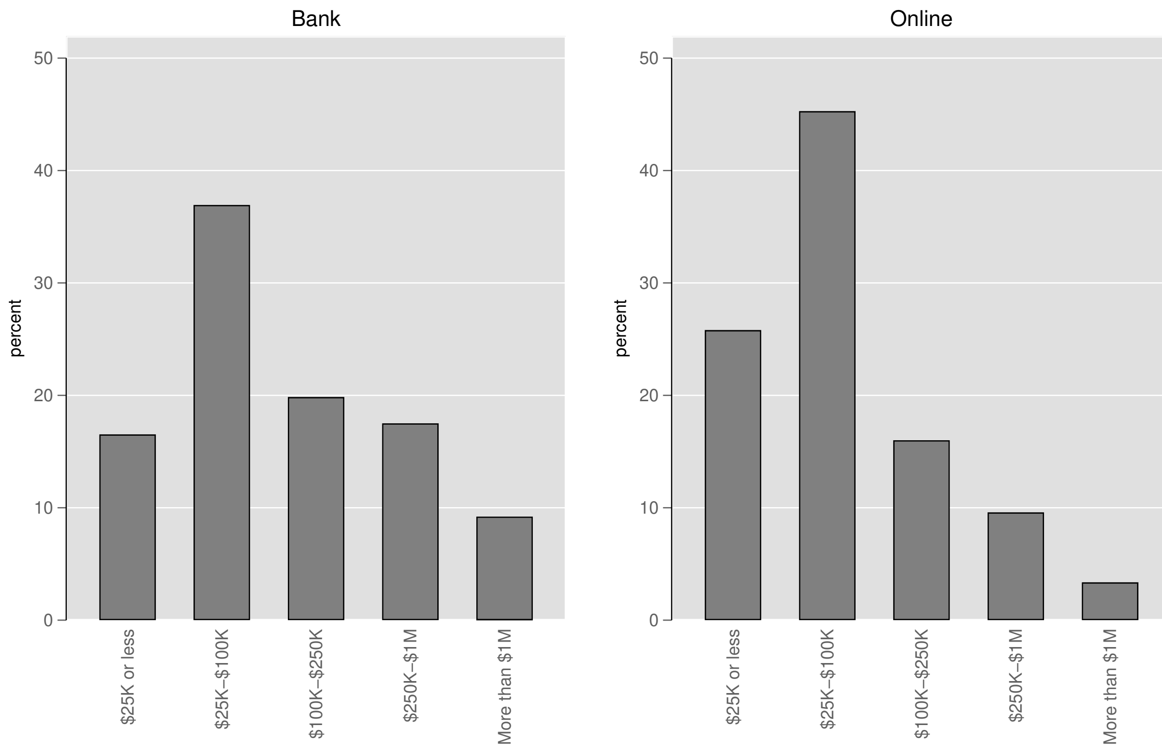


Figure 5: Distribution of Loan Size after Inverse Probability Weighting.